UiT Norges arktiske universitet

School of Business and Economics

The Sunk Cost Fallacy and Risk-Taking Behaviour

Evidence from a computer game experiment

Martin T. Skognes and Hannah S. K. Noste

Master's Thesis in Economics SOK-3901 May 2020

Foreword

This master thesis marks the conclusion of our master's degree in economics at The School of Business and Economics at the University of Tromsø – The arctic university. As our studies come to an end, we would like to express our gratitude towards the staff for all the great lectures and guidance along the way. There are a few people that deserve special appreciation, among which is our supervisor Andrea Mannberg, who orchestrated the project, as well as giving us theoretical input and excellent counselling throughout the year. A big thank you also goes to the rest of the team, namely Espen Sirnes who coded the game and helped with our statistical analysis, Gerit Pfuhl who helped gather participants for our experiment as well as helping out running the experiment. At last, we would like to thank Eirik Heen for helping us with every little thing we could need for the last 5 years, as well as helping us with the experiment. We are very thankful for all of you being part of the project.

Abstract

We examine whether behavioural sunk costs are related to an increased willingness to make risky decisions. Rational agents' decisions should not be contingent on sunk costs; however, foregoing research suggests that individuals in fact do react to such costs. Few studies have examined behavioural sunk costs and risk-taking with "real stakes", which is an important topic of research as many projects require investments in time and effort. If it is the case that behavioural sunk costs influence risk-taking decisions, it will be a particularly important finding in the field of risk-taking in avalanche terrain, as these types of activities are associated with large behavioural sunk costs. Our analysis is based on data from an experiment held at the start of 2020, with participants (N=65) from the psychology faculty at the University of Tromsø – The Arctic University of Norway. We are unable to find evidence of sunk cost effects. We do, however, find that risk-taking falls with time spent playing the game. This finding can either represent a learning effect or perhaps a reversed sunk cost effect.

Keywords: *Risk-Taking Behaviour, Sunk Costs, Avalanche, Experiment, Decision-making*

Table of Contents

Figures

Tables

1 Introduction

Why do people actively expose themselves to conceivably fatal risks? Multiple reasons come to mind, as the question has numerous valid answers. A potential explanation lies in the risk preferences, as it could be the case that their perceived rewards outweigh their perceived costs. Alternatively, it can be related previously incurred costs, where the individual feel as if his prior investment obliges him to advance with his risky endeavour. This is referred to as the sunk cost fallacy and is the focus of this study. More specifically, we analyse the link between non-retrievable investments in time and effort, i.e., behavioural sunk costs (BSC), and risk-taking behaviour in a computer game with monetary incentives.

Economists study the sunk cost effects because of the inefficient use of personal and social resources these effects contribute to. In preceding literature, there is ample evidence of sunk cost effects in various settings (Arkes & Blumer, 1985; Ashraf, Berry, & Shapiro, 2010; Friedman, Pommerenke, Lukose, Milam, & Huberman, 2007; Tan & Yates, 1995). However, the majority of these studies focus on monetary sunk costs (Arkes & Blumer, 1985; Ashraf et al., 2010; Roodhooft & Warlop, 1999), and few consider non-hypothetical risky behaviour. The literature on the effect of BSCs on risk-taking behaviour with real stakes is limited. Our analysis contributes to the literature in that we examine these sunk cost effects in affiliation to risk-taking with various degrees of risk. Additionally, we examine these sunk costs in terms of effort (time) spent rather than in monetary means.

There are several reasons as to why a study of the link between BSC and risk-taking behaviour is of interest. Perhaps most importantly, many risky projects require substantial initial investments in both time and effort. Examples include research projects and relationships. Another example is backcountry skiing in avalanche terrain, which generated the idea for this Master thesis. This is an interesting topic of research, as backcountry skiing has vastly increased in popularity over the past decades (Birkeland, Greene, & Logan, 2017). The stakes related to backcountry skiing can be high, even fatal, as can be observed from the increased number of fatalities as a result of avalanches. The majority of these cases are recreationalists (Birkeland et al., 2017). Another implication of avalanches is the considerable external costs associated with them. An avalanche may injure both the triggering individual, the other recreationalists in the area, as well as others responding to the accident. Search and rescue teams may also be taxed to their capacity with increased accident rates. Further, human triggered avalanches may cause severe damage to the forestation and infrastructure in the nearby area. As the implications regarding backcountry skiing and avalanches cause such extensive effects, individuals, the winter recreation industry, as well as society as a whole share a common interest in reducing both the social and economic costs of such accidents. Identification of various factors that potentially encourage risk-taking behaviour may assist in determining which groups are exposed to these accidents, and by recognising the psychological drivers, such as the sunk costs, we could reduce the number of fatalities altogether.

In this thesis, we test if BSCs increase risk-taking behaviour in a computer game with monetary incentives. In other words, the research question we aim to answer is “Do the increased effort (increased sunk costs) contribute to a higher willingness to take risk?”.
The computer game “Run to (and up!) the hills” (RTH) was designed to resemble a backcountry tour. Briefly summarised the game consisted of several trials where the participants were to ascend a mountainside with a given risk of falling. Each mountain contained a sunk cost represented by the effort required to get to the foot of the mountain, and our goal was to monitor how these approaches affected the number of steps a participant is willing to climb. The level of risk and the length of the approach were randomised for each trial.

This remainder of this thesis is composed as follows. In the subsequent section, part 2, we take a deeper look into the theories of relevance to our thesis, namely the neoclassical microeconomy and the prospect theory, in addition to the psychological drivers mental accounting and cognitive dissonance. Part 3 consists of a presentation of the previous literature, where we examine the sunk cost-findings of the preliminary research. Part 4 consists of our methodology; our experimental design as well as the econometric approach. In part 5 we present the results of our analysis. Part 6 provides a discussion of the aforementioned results, and part 7 is our concluding remarks.

2 Theoretical foundations of the sunk cost fallacy

Up until the introduction of Prospect Theory (Kahneman & Tversky, 1979). Expected Utility Theory dominated the analysis of decision-making under risk. In this section, we first provide an overview of the assumptions behind and implications of expected utility theory and show that this theory is unable to account for the sunk cost fallacy. We thereafter provide an overview of Prospect Theory, before examining some potential psychological drivers, namely Cognitive dissonance, Thaler (1980) "Mental Accounting" model, and Ambiguity aversion, which can explain reactions to sunk costs.

2.1 Neoclassical microeconomy

The Von Neumann-Morgenstern utility function is often considered to be the predecessor of the expected utility theory. The theory shows that under certain axioms of rational behaviour, a decision-maker facing probabilistically risky outcomes will act as if he maximises expected value of some function defined by the potential outcomes at a particular point in the future. The formulation follows four axioms that define a rational decision-maker:

Completeness: An individual is assumed to have well-defined preferences.

For any lottery resulting in A or B, it follows one of the following:

$A \prec B, B \prec A$, or $A \sim B$

So, either A or B is preferred to the other, or the individual is indifferent between the alternatives.

Transitivity: Introducing a third option, preferences will still be consistent, and the individual will still be able to rank them reasonably.

If $A \prec B$ and $B \prec C$, it follows that $A \prec C$

Continuity: There is a "tipping point" between being superior or inferior to a middle option.

If $A \lesssim B \lesssim C$, there is a probability $p \in (0, 1)$ such that

$pA + (1 - p)C \sim B$

The left-side notation, A is received with a probability p, whereas C is received with a probability $1 - p$. There thus is a possible combination of A and C making the individual indifferent between the mix of these and alternative B.

Independence: Independence of irrelevant alternatives states that a preference holds regardless of the possibility of some other outcome.

For any C and $p \in [0, 1]$;

$A \lesssim B \rightarrow pA + (1 - p)C \lesssim pB + (1 - p)C$

The third option, C, is therefore irrelevant meaning that the preferences between A and B holds, despite the presence of C.

If all axioms are satisfied, an individual is considered rational, and his preferences can be quantified to each outcome meaning that choosing the best lottery according to his preferences is the same as choosing the lottery with the highest expected utility. This is often referred to as the Von Neumann-Morgenstern utility representation theorem (1944) and is presented mathematically in Appendix A.

By usage of the axioms, we can look further into risk aversion. Assume that $U(x)$, with $U'(x) > 0$, represents the utility of wealth for an individual, and that the individual has an initial endowment equal to x_o. Suppose now that the individual is offered a gamble, in which the individual can win m with 50 percent probability and lose m with 50 percent probability. The expected utility of this gamble is then:

$$E_A[U(x)] = \frac{1}{2}U(x_0 + m) + \frac{1}{2}U(x_0 - m) \qquad (1)$$

Note that the expected value of this fair bet is equal to $E(\frac{1}{2}(x_o + m) + \frac{1}{2}(x_0 - m)) = x_0$. An individual is defined as *risk averse* if the expected utility of the gamble is smaller than the utility of the expected value of the gamble, i.e., if $U(x_0) > E_A[\mathrm{U(x)}]$. The individual is *risk loving* if the expected utility of the gamble is greater than the utility of the expected value of the gamble, i.e., if $U(x_0) < E_A[\mathrm{U(x)}]$. Finally, the individual is *risk neutral* if $U(x_0) = E_A[\mathrm{U(x)}]$. By Jensen's inequality, any concave utility function is associated with risk averse preferences. In other words, if the marginal utility is globally diminishing in x, then the individual is risk averse. Figure 1 demonstrates how an individual evaluates the offer of a fair gamble (A).

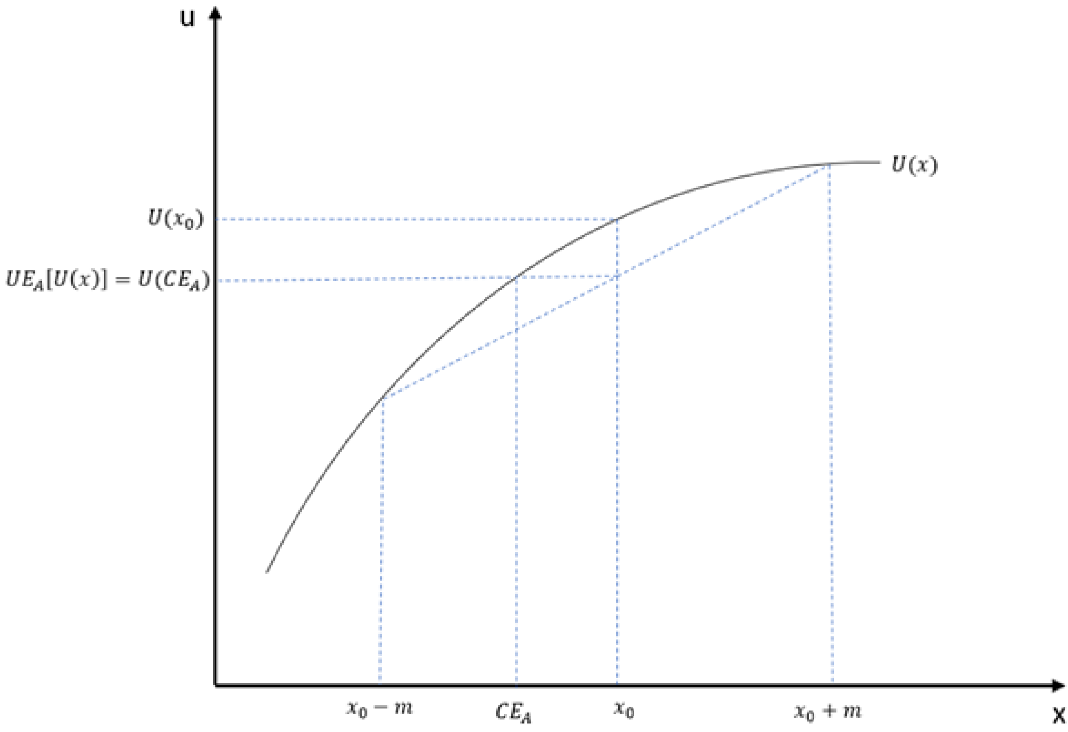

Figure 1 - Utility of x facing a fair bet

As the utility function is concave, and thus exhibits diminishing marginal utility of x, the individual would decline fair bets. The expected utility, $E_A[U(x)]$, from the gamble is less than the expected utility, $U(x_0)$, from keeping the original value. The individual would accept a trade of A for the certainty equivalent CE_A, which is considerably lower than that of x_0. Consequently, a risk averse individual is better off receiving a given amount with certainty rather than the same amount on average but with variance around this quantity.
In conclusion, classical theory predicts that an individual's preferences are consistent and assume that individuals evaluate the final outcome. An individual is presumed to be either risk averse, risk neutral or risk loving.

2.1.1 Sunk costs in a classical economics framework

According to economic theory, rational agents maximize utility by equating marginal utilities to marginal costs. This means that the individual should ignore preceding costs and only account for forthcoming costs and benefits. At all times, the optimal decision relies solely on current alternatives and future repercussions (Leeds, Leeds, & Motomura, 2015). Because all actions are affected equally, sunk costs should, in theory, not affect the decisions made, as they are irrevocably incurred regardless of which future action is favoured (Bernheim & Rangel, 2007). This is illustrated in figure 2 below, where C_1 and C_2 represent two total cost functions associated with the production of some good or activity, x. The two cost functions have different levels of fixed costs but equal marginal costs. B represents the total benefit associated with the production of x.

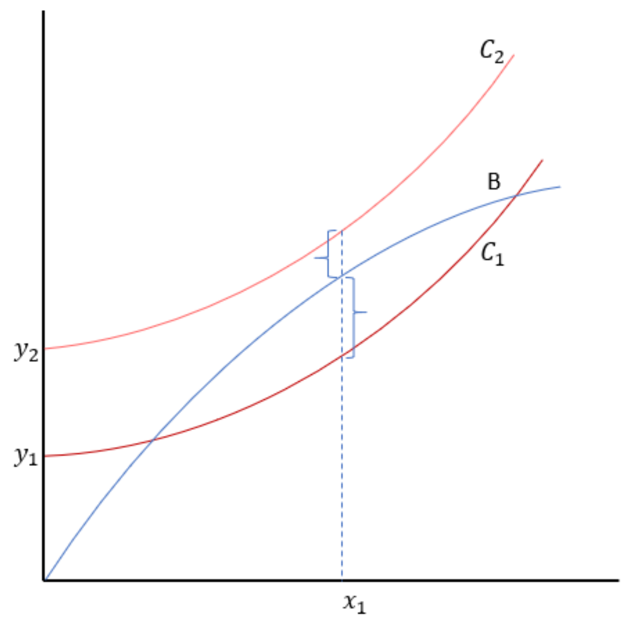

Figure 2 - Optimal choice with sunk costs

Despite the varying degrees of sunk costs incurred, it is irrelevant for which choice is optimal. This is because the distance between the cost curve c_1 and the benefit curve is at its largest at the point x_1. This aspect stems from thinking on the margin: because the sunk cost is present regardless of everything else, it has no effect on the marginal costs. This, of course, is also true in the case where the sunk costs are large enough to make the total costs exceed the total benefit, as is the case for c_2, as it yields the minimum loss. This observation demonstrates the general point that "sunk costs never affect a decision maker's best choice". In conclusion, classical economic theory cannot explain situations in which people react to sunk costs. However, as pointed out by both Arkes and Blumer (1985) and Thaler and Johnson (1990) Prospect Theory (Kahneman & Tversky, 1979), can.

2.2 Prospect theory

The paper published by Kahneman and Tversky (1979) questioned several decision-making problems in which preferences methodically defied the axioms of expected utility theory. Considering these findings, they argued that the utility theory was not a sufficient descriptive model and came up with an alternative approach, the prospect theory. The theory was originally designed for straightforward prospects with monetary outcomes and stated probabilities but has since been extended to include more involved choices.

Prospect theory has two distinct aspects of the choice process: an editing phase and an evaluation phase. The former includes a preliminary analysis of the prospects presented, whereas the latter includes a choice in which the prospect with greatest value is chosen. The comprehensive value (the expected utility) of an edited prospect, denoted as V, is articulated in terms of two scales, π and v. The first scale, π, is a decision weight associated with the probability p, reflecting the overall impact of p on the value of the prospect. π is however not a measurement of probability, and $\pi(p) + \pi(1 - p)$ typically subceeds unity. The second scale, v, appoints a number $v(x)$ to each outcome variable x, expressing the subjective value of that outcome. Outcomes are characterised relative to the reference point (serving as the zero point), implicating that v determines the magnitude of the deviations from that reference point. The formulation presented by Kahneman and Tversky only concerned transparent prospects of the form $(x, p; y, q)$, which at most contain two non-zero outcomes. In this formulation, an individual receives x with the probability of p, y with the probability of q, and receive nothing with the probability of $1 - p - q$, where $p + q \leq 1$. A prospect is strictly positive only if all outcomes are positive, I.E. $x, y > 0$ and $p + q = 1$. It is however strictly negative if all outcomes are negative. A normal prospect is neither strictly negative nor strictly positive.

There are three important characteristics of the value function: it must be (i) defined on inconsistencies from the reference point; (ii) generally be concave for gains and convex for losses; (iii) be steeper for losses than for gains, all in which are illustrated in Figure 3 below.

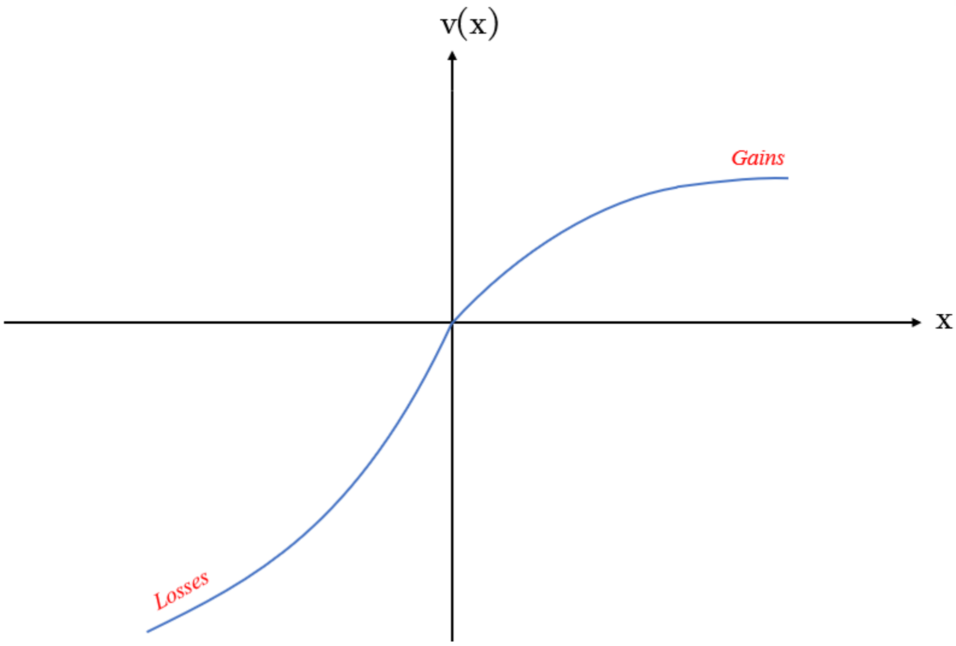

Figure 3 - Value function

Now, consider the formulation by Kahneman and Tversky, in which a prospect $(x, p; y, q)$ is a gamble yielding x with probability p and y with the probability q. According the Prospect theory, if x and y are of opposite signs ($x \geq 0 \geq y$ or $y \geq 0 \geq x$), the prospect's value (V) is given by:

$$V = \pi(p)v(x) + \pi(q)v(y) \quad (2)$$

However, prior to the valuation the prospects are simplified in the editing phase. In addition, the editing phase includes an evaluation rule differing from that of equation (2) for strictly positive or strictly negative alternatives. The prospects are segregated into two components: (1) the riskless component, i.e., the guaranteed minimal gain or loss; (2) the risky component, i.e., the additional gain or loss at stake. Thus, if either $x > y > 0$ or $x < y < 0$, then

$$V = v(y) + \pi(p)[v(x) - v(y)] \quad (3)$$

The value of a strictly positive or strictly negative prospect is equivalent to the value of the riskless element in addition to the difference in value between the outcomes, multiplied by the weight correlated to the more extreme outcome. The fundamental aspect of equation (3) is that the decisive weight is applied to the value-discrepancy $v(x) - v(y)$ (The risky element), but not to the riskless element, $v(y)$.

Aforementioned characteristic of the prospect theory is that of loss aversion, where it is suggested that the gains are overshadowed by potential losses. People generally see a 50/50 bet as an undesirable one, and this aversiveness of symmetric odds tend to expand the extent of the stakes. That is, if $x > y \geq 0$, $(y, .50;\ -y, .50)$ is favoured to $(x, .50;\ -x, .50)$, and therefore in correspondence to equation (2),

$$v(y) + v(-y) > v(x) + v(-x) \quad \text{and} \quad v(-y) - v(-x) > v(x) - v(y)$$

Setting $y = 0$ yields $v(x) < -v(-x)$ and allowing y to converge toward x yields $v'(x) < v'(-x)$, given that the derivative of $v(v')$ exists. The value function for losses is thus steeper than that for the gains.

Correspondence of the sunk cost effect and prospect theory suggests that prior investments are not completely discounted. In such cases, prospects are not perceived from the status quo (the origin), but rather from a point on the loss side of the value function. In other words, prior investments are identified as a loss and affect the decision-maker in the evaluation of successive prospects. Further, as a consequence of the convex shape of the value function, additional losses do not extensively decrease the value, whereas gains, on the other hand, generate substantial increases in value. As a result, further investments to the sunk cost is therefore likely to transpire rather than complete withdrawal.

2.3 Psychological drivers

Foregoing literature heavily focuses on the psychological drivers in the manifestation of the sunk-cost fallacy. Among these drivers are that of mental accounting and cognitive dissonance.

The theory of mental accounting (Thaler, 1980) revolves around its framing. Decision-makers mentally “frame” their resources, transactions, money, etc to derive what they feel are their optimal levels of utility or loss-minimisation. The theory also states that people mentally categorise their money and resources based on pre-determined categorisation such as purpose, usage, and so on. Money and resources are therefore not considered to be interchangeable between these accounts and are evaluated based on their origin and intended usage (Thaler, 1985, 1999). Mental accounting contravenes with the normative economic principle of fungibility which suggests easing of the transferability and substitutability between resources. Within behavioural economic, questions such as the one Kahneman and Tversky (1984) discussed, that is “Why do more individuals spend 10$ on a theatre ticket if they had just lost a 10$ bill than if they had to replace a lost ticket worth 10$?”, or in Thaler’s earlier work, “Why are people more likely to spend a small inheritance and invest a larger one?” (Thaler, 1985). Mental accounting goes a long way in answering these questions, as individuals separately make decisions for each account and are therefore losing out on the entire perspective of the portfolio. Mental accounting is also closely related to the sunk cost fallacy. By spending money on something, mental accounting makes us feel as if we have to get something out of our purchase.

Another psychological driver is cognitive dissonance (self-justification). People generally have a hard time admitting their previous mistakes (Staw, 1976), and need to appear rational in the eyes of both others and themselves. As a result, individuals are prone to stick to their initial course of action despite the moderate likelihood of success. Chung et al. (2018) argue that the cognitive dissonance of decision-makers is a result of initial investment decisions in an unfavourable alternative. They suggest that cognitive dissonance plays an instrumental role in the relationship between sunk costs and further investments in the project, as the best way to justify prior investments is to pour resources into it.

3 Previous empirical findings on the sunk cost fallacy

The sunk cost fallacy has previously been studied in both economics and psychology. In psychology, the sunk cost fallacy is often referred to as "escalation of commitment" (Thaler, 1980). The sunk cost fallacy is today a relatively established concept. However, as we will see, the empirical evidence on the existence of such a fallacy is mixed. In this section, we review three strands of the literature: studies focusing on monetary sunk costs, sunk costs and risk-taking behaviour, and studies of behavioural sunk costs.

3.1 Monetary sunk costs

Arkes and Blumer (1985) wrote one of the most cited papers documenting the sunk cost fallacy. They examined the sunk cost effects through 10 different experimental designs, among which were questionnaires, hypothetical scenarios and field experiments. Based on their field experiment, they were able to capture disparities in behaviour amidst three groups of theatre season ticket holders, who at random were separated into three different price categories: full price, and two levels of discounted prices. The experiment showed that the ticket holders facing full-priced tickets were prone to visit the theatre more regularly during the season than those who faced a discounted price. Further, by the usage of situational questionnaires, they discovered that people with experience in economics were as likely to fall prey to the sunk cost fallacy as those without the experience. They also discovered an increased willingness to invest in the presence of sunk costs. They interpret these results as if the investor does not want to see the investments already completed going to waste.

A study by Roodhooft and Warlop (1999) conducted a field experiment in which they presented hypothetical scenarios to managers of Belgian hospitals and rest homes in which they had to make a decision regarding outsourcing of patient catering to external sources. Their results showed a significant under-engagement by hospital managers in outsourcing of catering services when asked to envision a scenario where they before the outsourcing-decision had an in-house catering of meals. The effect was significantly enhanced when they were presented with information that in the event of outsourcing, a caterer specific investment would have to be made. Ashraf et al. (2010) investigated sunk cost effects on health product use in Zambia. They used a similar mixed approach as Arkes and Blumer (1985) with both hypothetical questions and a field-based experiment. Ashraf et al. (2010) find significant sunk cost effects when respondents answer hypothetical questions, but no effects when stakes are real. In other words, the Ashraf et al. (2010) study is consistent with the findings of Philips et al (1991).

3.2 Risk-taking behaviour

The seminal work by Thaler (1980) and Thaler and Johnson (1990) suggested that sunk costs induce loss aversion, and therefore give rise to risk-loving preferences. However, empirical research on the link between sunk costs and risk-taking behaviour is relatively scant.

Knox and Inkster (1968) analysed risky behaviour among horse-race gamblers. They conducted two experiments in which they interviewed several individuals regarding their optimism before and after placing a bet. Their results showed that gamblers were often more optimistic right after committing to the bet, thus yielding evidence of the sunk cost fallacy in real-life situations. Phillips et al. (1991) used a set of lottery experiments to test for the sunk cost fallacy. In one experiment, participants were put in a hypothetical scenario where they for a given budget had to decide how many lottery tickets they wanted to buy. In a second experiment, participants were given the same instructions but were now asked to physically pay for the lottery tickets. The sunk costs were introduced in the form of the participants being able to buy more tickets after purchasing the initial ticket. Phillips et al. (1991) found that, while most participants fell prey to the sunk cost fallacy in the hypothetical choice experiment, a substantially smaller share reacted to sunk costs when the stakes were real. Additionally, they looked at the risk preferences of the participants. They did so by letting the participants value the lottery tickets themselves in the hypothetical scenario, and thereafter defining the individuals risk preferences based on the prices they chose.

Whyte (1993) examined the escalation of commitment based on the prospect theory of Kahneman and Tversky (1984). Six scenarios were presented to the participants in which substantial prior investments had been made to a failing course of action. As a control decision frame, a high risk, high return investment alternative is presented. The sunk cost decision frame exhibits an identical investment to that of the control decision frame, but sunk costs have been incurred to the project in question. Additionally, participants were asked to quantify the level of risk they were willing to take to rescue the failing project. Whyte (1993) were able to find evidence of the sunk cost fallacy consistent with the prospect theory as well as evidence of self-justification.

3.3 Behavioural sunk costs

Although the term sunk cost include investments in money, effort or time (Arkes & Blumer, 1985), previous research of the field primarily focuses on how prior financial engagements affect subsequent decisions. However, a few studies have investigated the effect of BSCs, we review these below.

Building on the findings of Thaler (1980), Zeelenberg and van Dijk (1997) stated that sunk costs could result in risk aversion based on the decision-makers aspiration. The participants were predicted to be more risk-averse in gain-situations than in loss-situations. They did this by making an experiment in which the participants were presented with eight different scenarios, where some included behavioural sunk costs, while others did not. In the outcome game, the participants were presented two alternatives: a secure option (yielding 50 guilders) and an insecure option (yielding a gain of 100 guilders, or a gain of 0 guilders), and vice versa when examining losses. Their results corresponded to the prospect theory, and the participants were more risk-averse in terms of gains, and less risk-averse in terms of losses. Incurring BSCs appeared to increase risk-aversive choices, i.e., they were able to find a reverse sunk cost effect. Simon (1955) suggested that individuals simplify alternatives by viewing the outcomes as satisfactory is above the aspiration level, and deficient if they were below it. Therefore, aspiration levels may be satisfied by both risk-seeking and risk-averse choices, and the phrase “Too much invested to quit” can thus in some cases be rephrased as “Too much invested to gamble” (Van Dijk & Zeelenberg, 2003).

Soman (2001) used surveys to examine the relationship between sunk costs in the form of time and monetary sunk costs and concluded that people may perceive costs in time and money differently. Soman (2001) conducted six experiments, in which the participants were presented hypothetical scenarios with varying sunk cost measurements (time and money). Altering the size of the investments to the sunk cost fallacy did not affect the results. Soman (2001) gave three explanatory reasons as to why this was the case; (1) Time cannot be inventoried or replaced; (2) Time is not aggregated as conveniently as money; (3) Accounting for money is a conventional exercise, whereas accounting for time is not.

Friedman et al. (2007) designed a game to isolate determining factors of the sunk-cost fallacy. Subjects were instructed to use “clicks” from a given budget to reveal treasures on islands. The participants had a fixed “click” budget, and to get to the islands the participants encountered a sunk cost, which was either set to high (12 clicks) or low (0 clicks). The number of treasures on each island was not affected by the sunk cost. They tested for several different treatments with different information revealed, “click-budgets”, sunk costs and participants with and without experience. As for the results, there are some mixed results. The click overall difference for all the treatments was -.17, which indicated a slight reverse sunk cost effect (but this was not significant). There were a total of four cases, in which only one (case 1) yielded evidence of the sunk cost fallacy. In case 1, the participant was presented with the island value upon arrival with a “hit probability” (likelihood of finding a treasure) was approximately 8 %. The cases were more or less identical, with some minor alterations separating them. There was some evidence for the sunk cost fallacy in case 1, with the high sunk cost lead to a more frequently stubborn error. A problem with their study was that they examined numerous explanatory factors, which made the formal analysis complicated. With all the factors and treatment in the experiment could it be difficult to explain the sunk cost by itself, as they focused on finding the optimal search strategy.

Sweis et al. (2018) conducted an experiment with humans, rats and mice. The goal was to test the sensitivity to sunk costs, across species. Their study involved a restricted time-budget of 30 minutes in which the participant had to progress between various reward stations. The players were rewarded with four-second films of various genres (dancing, cute animals, etc.), whereas the animals were rewarded with food. At the beginning of each round, the participant was given an offer in the form of information about the topic of the film. If the offer was declined, the participant moved on to the next gallery and was again given an offer. If, however, the offer was accepted, the participant was directed to another room, where he had to wait for the film to be downloaded (sunk-cost treatment). The probability of collecting an award once accepting an offer relied on how much time was left until the reward was given (prospective costs) and by the time already waited (the sunk cost). They discovered that the sunk costs had an overall robust effect which increased with further investments.

3.4 Conclusions from previous research and link to the current study

In summary, classical economic theory predicts that costs that have already been sunk will be ignored in future decisions. Several empirical studies contradict this prediction and show that, in many situations, people react to sunk costs. However, previous research does not unambiguously prove that people always fall prey to the sunk cost fallacy, or that sunk costs inflate incentives to make risky decisions. Few studies experimentally test for sunk cost effects with real stakes. Even fewer investigate the link between BSCs and risk-taking behaviour. Those who do, find no or very weak support for the sunk cost fallacy. Our study aims to fill this gap.

Our empirical approach builds on the work by Friedman et al. (2007) and Sweis et al. (2018). Friedman’s study attempts to capture the sunk cost effects, but includes too many variables, making it hard to fully capture the sunk cost effects. Additionally, there is no inclusion of risk in the study. The study of Sweis et al. captures the sunk cost effects but do however not focus on risk, which is an aspect we intended to implement in our study.

4 Methodology

We use an experiment with monetary incentives to identify the effects of BSCs on risk-taking behaviour. Incentivised experiments allow researchers to identify effects via exogenous and randomized treatments, making it possible to identify causal effects. The use of incentivised choices increases the chance of truthful response (Croson, 2005). Some general guidelines apply to economic experiments making them differ from psychology: deception is prohibited – Psychological experiments tend to have ulterior motives, whereas economic experiments seek to examine exactly what is presented to you, and no alterations of the experiment are allowed; incentives are required, usually through a monetary benefit; the participant is given as little context as possible (Croson, 2005). We describe our sample of participants, our experimental design and procedure, and our statistical approach, below.

4.1 Measurement instruments

In this section, we describe how we operationalise risk-taking behaviour and sunk costs in the experiment. We describe the details of the computer game in section 4.3, below.

4.1.1 Risk-taking

We base our risk-taking instrument on two established measurement instruments, the Balloon Analogue Risk Task (BART) and the Columbia Card Task (CCT).

The BART experimental design was first introduced by Lejuez et al. (2002) to better understand the reasoning behind risky behaviour. The experiment takes the form of a game, where the participant sequentially makes decisions of whether or not to keep pumping a balloon. Each pump yields a monetary reward, and the participant can choose to stop whenever they want, “storing” the rewards. At the start of the game, the player is informed that there is a risk that for each pump the balloon may explode, leaving him empty-handed for that particular round.

A common result is that individuals generally are risk-averse, suggesting that their respective risk-return payoffs are not being maximised. The participants tend to pump the balloon significantly less than that of the optimal strategy (Campbell, Samartgis, & Crowe, 2013; Fukunaga, Brown, Bogg, & Fukunaga, 2012; Lejuez et al., 2003; Lejuez et al., 2002). A further increase in the monetary rewards yielded an even lower number of pumps per trial (Vigil-Colet, 2007). Individuals characterised as impulsive and sensation-seeking were considered less likely to be affected by changes in the monetary rewards, a finding which was backed up by a study conducted by Humphreys, Lee, and Tottenham (2013). Their study showed that sensation-seeking individuals on average pumped the balloon more and was thus more prone to explosions. In BART, the increase in pumps is perceived negatively, as it is correlated to nonadaptive demeanour. This is in contrast to the fact that the more risk-seeking individuals are closer to the optimal number of pumps. Each pump yield proportionally lower rewards than the previous pumps, so the gain has diminishing marginal value. Furthermore, the risk is increasing with each pump, where each pump is connected to an increased probability of the balloon exploding. BART has been proved to correlate with risk-taking behaviour and has therefore provided a solid baseline for our experimental design. An implication of BART, however, is that the balloon always explodes, be it after one pump or hundred.

Much like that of the BART framework, the Columbia Card Task (CCT) is an experimental design constructed to examine individual risk preferences (Figner, Mackinlay, Wilkening, & Weber, 2009). The experiment can be divided into two categories: CCT hot and CCT cold. Both versions are played with 32 cards, displayed in four rows of eight cards. Each game has several trials, where each trial ends when the player picks a loss-card or choose to collect their winnings for that particular round. When the trial ends, the player advances to the next trial until the game eventually ends. Each card can either represent a loss or gain. If the player encounters a loss-card, all rewards for that round will be lost, and the player moves on to the next trial. This process is repeated until the game ends. For each trial, the participant is presented with information about the number of loss cards, the payoff, and which trial they are currently playing regardless of which version of the game is played. The probability of facing a loss is proportionally increasing with each chosen card, while the total payoff simultaneously is increasing. This implies that the more cards turned, the greater the risk, suggesting that the number of cards turned on average is a good indicator of individual risk preferences. In economic theory, with rational (and risk-neutral) individuals, the optimal strategy is to turn cards until the expected value of turning the next card no longer is positive. CCT hot is played with the participant making stepwise decisions about whether to turn an additional card or not, where they are given instant feedback about their choices. The total accumulated rewards are visible to the player at all times, which continuously increases/goes back to its initial value depending on whether or a loss or gain card is chosen. The odds of picking a loss card increases with every chosen card so that the participant continuously need to update his faced probability. A benefit of the CCT procedure is that the reactions to risk easily can be evaluated, as each trial may contain a different amount of loss cards. CCT is through various studies shown to correlated with risk-taking behaviour (Buelow, 2015; Figner et al., 2009). However, a problem with the CCT is that it is common practice to rig the game such that the participants do not encounter loss cards. This strategy increases the number of valid observations but reduces the quality of the data since participants may realize that the game is rigged.

The measurement instrument for risk-taking behaviour in the Run to the hills game resemble both the BART and the CCT. In our game, the participants make sequential decisions on how high to climb on a mountain. Each step is associated with a monetary reward, and with a risk of falling. In contrast to the BART and CCT, the risk and reward remain constant for each step, and we do not rig the game. In other words, there is no deception and participants can reach the summit of the mountain without falling.

4.1.2 Risk preferences

Risk and uncertainty play an instrumental role in more or less every economic decision. Consequently, understanding individual risk preferences is closely related to understanding and predicting economic behaviour. To measure these preferences, we used the framework of Dohmen et al. (2011) which shows that domain-specific measures are better at predicting risk-taking behaviour, i.e., questions regarding sports predict risk-taking in sports, questions regarding financial risk predicts financial risk-taking, etc. Our game considers a situation in which participants climb a mountain for monetary rewards. Before the experiment, we were unsure of which class of risk preferences best suited our analysis, be it sporting, financial or general risk. For each category, the participant was asked questions about their risk preferences:

Attitude to risk (Dohmen et al., 2011) (0 = not willing to take on risk at all, 10 = very eager to take on risk)

> *Generally speaking, are you a person who is ready to take on risk, or are you a person that tries to avoid it?*
>
> *0 1 2 3 4 5 6 7 8 9 10*

Similar questions were asked in relation to both financial and sports- and outdoor activities.

4.1.3 Sunk costs

Our instrument for sunk costs is based on Sweis et al. (2018). Their study involved a restricted time-budget of 30 minutes in which the participant had to progress between various reward stations, where the participants got to a location and had to wait for 1 – 30 seconds before being rewarded with a short film. At any given time (also during the waiting period), they could abandon the location and travel to the next one. The sunk cost effects were measured for those occasions in which the participant waited out the entire delay.

In our game, we introduce sunk costs in the form of different approach lengths to each mountain. More specifically, the sunk cost is in reference to time and effort, where the participants have to click through each step of the approach. In contrast to the Sweis et al. (2018) design, we used a design where participants were unable to skip the approach to the mountain, as this would likely make for few observations of the longest approaches.

4.2 Experimental design

In Run to (and up!) the Hills, players earn money by climbing as many mountains they can within a given time constraint. The player sequentially decides how far up a mountainside he wants to climb. Each step is associated with a constant monetary reward. The player thus earns more the higher he climbs. The caveat is that the player can fall down the mountain and lose all prior earnings on that mountain. The risk of falling is constant for all steps and known by the player. A trial may end in one of three ways: (1) The participant chooses to stop the trial, and move on to the next mountain, (2) he falls from the mountain, or (3) he reaches the summit of the mountain. In either case, as long as there is still time in the time-bank, he moves on to the next mountain. To make the game more captivating for the participants, mountains vary in both appearance and name.

The computer game was designed by economists and psychologists at UiT in collaboration with George Loewenstein at Carnegie-Mellon University. Each trial of the game had two phases: an approach phase, and a climb phase. All participants played at least 6 trials.

Phase A – Approach: At the start of each trial, the participant was exposed to a sunk cost, i.e., the number of steps needed to reach the foot of the mountain. To move one step closer to the mountain, the participant had to hold down three keyboard keys (shift, c, and u) for two seconds. The approach could be short (2 steps), medium (10 steps) or long (20 steps), meaning that he would at minimum use 4 seconds to get to the foot of the mountain. The approach treatment was randomized over trials. During the approach there was no risk related to the steps, nor were there any profits to be made. The approach room is depicted in figure 4.

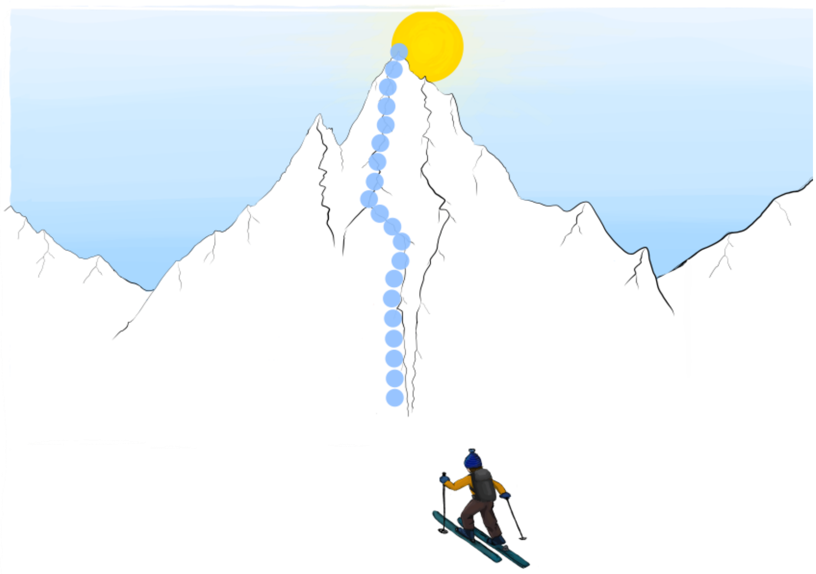

Figure 4 - Approach

Phase B – Climbing: Once the foot of the mountain was reached, the participant entered the "Climbing" room (figure 5). He was informed of the riskiness associated with that particular mountain. The risk could be either be high or low and was operationalised as the probability of stepping onto a trigger point. In the pilot version of the game, we used two levels of risk: 5 per cent, and 10 per cent. Once the climbing had started, the participant could at any given time decide to stop the trial, climb down from the mountain and move on to the next one. If he decided to stop without hitting a trigger point, his accumulated earnings were stored in the "bank", and he moved on to the next trial. If, however, he stepped onto a trigger point, all earnings acquired for the mountain were lost. Each mountain contained 20 steps, meaning that if the participant reached the summit, 20 NOK would be acquired. The participants had access to updated information on all relevant parameters, e.g., risk level, steps climbed, and distance to the summit, on each trial throughout the game. We also continuously provided participants with information about accumulated earnings and the time left. There was a total of six different treatments ($2x3$). These treatments included the three approach-lengths and the two levels of risk.

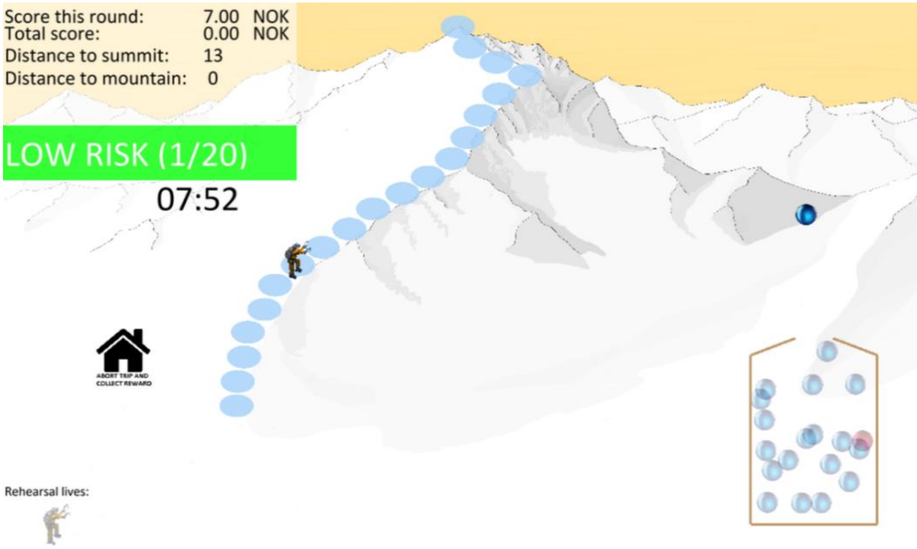

Figure 5 - Example of climbing phase

We would like to end this section with a brief comment on our representation of risk, i.e., our use of urns. Before the implementation of the game, we conducted a small ($N = 12$) survey at UiT. The survey aimed at testing different comprehension of risk using different visualisations of probabilities. We provided the participants with two types of examples, one using two dices, and one using urns with either 10 or 20 balls. For example

An urn contains 10 balls (9 black and one red). It is not possible to observe the colour of the balls through the urn.

A. *What is the probability (in percentages) that a randomly chosen ball is red?*

1% 5% 10% 15% 20% 25% 30% 35% 40% 45% 50%

55% 60% 65% 70% 75% 80% 85% 90% 95% 100%

The survey results showed that when using dices, people showed a greater understanding of the probabilities. 69% overestimated the probabilities when presented with the questions about dices, whereas the number fell to 50% when answering similar questions about urns. Most individuals did however correctly predict the probabilities in the case of urns containing 10 balls, which is our chosen measurement for the low-risk mountains.

4.3 Experimental procedure

We carried out the experiment in January 2020 on 65 second-year psychology students who participated in the experiment as a part of a course. In addition to the course credits, the participants could earn money in the game. The experiment was held in six sessions, with about 11 participants per session. The sessions took place in a computer lab at UiT the Arctic University of Norway. Each session started with a power-point presentation of the experiment and the structure of the game. These instructions were also handed out to each participant. After the introduction, each participant answered a short pre-experiment survey, which tested comprehension of the game. In this pre-questionnaire, we examined whether or not the participants understood the game based solely on the descriptions and tested their understanding of probabilities. We did this by asking multiple questions regarding potential payoffs and probabilities of falling in the case of both risk levels.

After the pre-experiment survey, all participants played three trials of the game. The trials aimed to familiarize the participant with the game. The participants were informed that they did not earn any money during trial sessions. After the trials, the real game session began. Each participant had a time budget of 20 minutes to climb as many mountains as s/he wished and earn as much money as possible. All participants played each treatment (high and low risk, short, medium and long approach) at least once. The order of treatments was randomized. At the end of the 20 minutes, the participant filled out a short post-experiment questionnaire, containing questions on socio-demographics and risk preferences. Each experiment session ended with participants collecting their earnings in a separate room.

Both the pre-experimental and the post-experimental questionnaires are presented in Appendix D.

4.4 Econometric approach

The main aim of the study was to evaluate whether the behavioural sunk costs affected risk-taking behaviour. The outcome variable for our main regression is the number of steps climbed, varying between 1 and 20 steps. We considered several models for our analysis, namely the Ordinary least squares (OLS), a Censored Poisson, and the Tobit regression model. OLS produces the best linear unbiased estimates (BLUE) on data that is continuous and normally distributed. Our data is censored at 1 and 20, and participants cannot take fractions of a step. Each participant played several trials of the game, thereby producing a panel dataset. Poisson models were developed to deal with count data, like ours. However, we were unable to find a censored Poisson model that could handle the panel structure of our data (i.e., the intra-individual correlation). Therefore, we opted to use a panel Tobit model. A Tobit model deals with dependent variables that in some way is censored. As our data was censored at each end of the interval, the Tobit model was an ideal fit. Our dependent variable is discrete, whereas the Tobit regression model deals with continuous dependent variables. However, as our dependent variable includes 20 different values, it is a fair assumption that it is approximately continuous.

The general representation of the regression is specified in equation (4) below.

$$y_{it}^* = \alpha + \beta_1 MediumSC_{it} + \beta_2 LongSC_{it} + \beta_3 HighRisk_{it} + \beta_4 Gender_i + \beta_5 Age_i + \beta_6 \, Time\_used_{it} + \beta_7 GRP_i + \beta_8 Exp_i + \beta_9 Understanding_i + \beta_{10} Probability_i + \varepsilon_{it} \tag{4}$$

$$y_{it} = 1 \; if \; y_{it}^* \leq 1$$

$$y_{it} = y_{it}^* \; if \; y_{it}^* > 1 \; and \; y_{it}^* < 20$$

$$y_{it} = 20 \; if \; y_{it}^* = 20$$

where, for individual i, y_{it}^* is a latent variable describing the number of steps climbed per trial. «MediumSC» and «LongSC” are dummy variables and represent the sunk cost treatments: medium approach and long approach. High risk is a dummy variable taking the value one if mountain I had a high risk (10 per cent) and zero otherwise. GRP is the general risk preferences. Both Gender and Age are socio-demographic variables describing the participants. Time_used is categorised in groups describing which quartile of the game each trial concluded. The Exp variable is a dummy variable stating whether the participant had experience backcountry skiing before the experiment. Both Understanding and Probability articulate if the participant understood the game itself and the probabilities related to it.

As each individual carried out several trials, we also had to cluster the IDs of each individual to make sure all participants were weighted equally. Additionally, this was done to handle the correlation for the specific individuals.

4.4.1 Adjustments and weaknesses in the data

To prepare the dataset for analysis, we first deleted all test trials. We further excluded all trials on which the participants fell down the mountain. The motivation for excluding falls is that we do not know how many steps the participant would have been willing to take on that particular mountain. These downward revisions of the sample meant that at the point of the main analysis, the data included 391 observations, as opposed to the 968 observations in the original data. All 65 participants are observed at least once in the dataset. However, since some participants fell down the mountain more often than others, and some used more time to climb a mountain, the number of observations (trials) varies between participants. It is also worth mentioning that due to an error in the code of the game we were unable to observe which step the participants fell, which further incentivised us to use only the completed trials.

Our limited sample size, in combination with the skewed age distribution in our sample, resulted in very few observations in some age categories. Therefore, to enable a (basic) test for age effects, we divided our sample into two larger age groups: 22 years old or younger, and older than 22 years old.

5 Results

In this section, we will first provide a descriptive analysis of the data, and thereafter present a regression analysis of the sunk cost effect. We end the result section with an analysis of a set of factors that can help understand the results of the study.

5.1 Descriptive analysis

The main analysis includes data from all 65 participants. We present descriptive statistics of the sample in Table 1 and 2.

Table 1 - Descriptive statistics (Background data)

Participants	**Total**			**Percentage**
Number of participants	65			100%
Male	15			23.1%
Female	50			76.9%
Age (<=22)	43			66.15%
Age (>22)	22			33.85%
Experience	**Median**	**Min**		**Max**
Ski days/season	0	0		41-50
Years of skiing experience	0	0		9-10
Risk preferences	**Mean**	**SD**	**Min**	**Max**
General risk preferences	4.88	1.74	1	10
Financial risk preferences	3.49	1.93	0	9
Outdoor/sports risk preferences	3.89	2.25	0	10

As can be observed from Table 1, our sample consists of relatively young individuals. About two-thirds of the sample is 22 years or younger. A majority of the participants are female (77 per cent). The descriptive statistics also reveal that the median participant has no experience of travelling in avalanche terrain. Only 22 per cent have at least two years' experience of backcountry riding, and 60 per cent say that they have no experience at all.

The participants are relatively symmetrically distributed in terms of attitude toward general risk (mean = 4.88, SD = 1.74). In terms of financial risk and risk related to sporting activities, the risk parameters, although not as cantered, exhibit similar results. This is indeed an interesting finding, as it shows the heterogeneity among the participants in terms of risk as this speaks to the spread of the sample. Based on a paired t-test we ran with all risk preferences, we were able to see that there were significant differences between the general risk preferences and both the financial ($p < 0.001$) and sporting risk preferences ($p < 0.001$), but not among the answers for the financial risk preferences and the sporting risk preferences ($p = 0.3$). Let us now turn to the descriptive outcomes of the game.

Table 2 - Descriptive statistics (The game)

The game	**Mean**	**SD**	**Min**	**Max**
Games (Total)	10.88	2.17	7	16
Games (Completed)	6.02	2.36	0	12
Steps climbed	7.87	4.71	1	20
Steps climbed (Risk)				
High risk	5.19	2.97	1	20
Low risk	10.49	4.62	1	20
Steps climbed (Approach)				
Short	7.62	4.46	1	20
Medium	8.08	4.92	1	20
Long	7.89	4.72	1	20
Total score	47.37	17.62	0	96
Earnings per game (Total)	4.47	1.71	0	9.60
Earnings per game (Completed)	8.45	3.31	0	15.67

The participants played on average 10.88 (NB – all trials, including the falls) trials of the game (min=7, Max =16). However, many trials ended in a fall. The average number of successful trials is only six in the sample. The spread in the number of successful trials is relatively large (min =1, max =12). On average, participants climbed about 8 steps per completed mountain and thus earned about 8 NOK. As observed in Table 1B, neither the means nor the standard deviations differ much among the various approaches.

The number of steps climbed correlated to the risk of the mountains is presented below. The participants averaged substantially fewer steps per trial with high risk (5.19) than on trials with low risk (10.49). Both of these results are substantially lower than that of the optimal strategy would suggest (20 steps for low-risk mountains, 10 steps for high-risk mountains). Calculations for the optimal strategy can be found in Appendix C. On average, the participants faced more or less the same number of low-risk (2.97) and high-risk mountains (3.04).

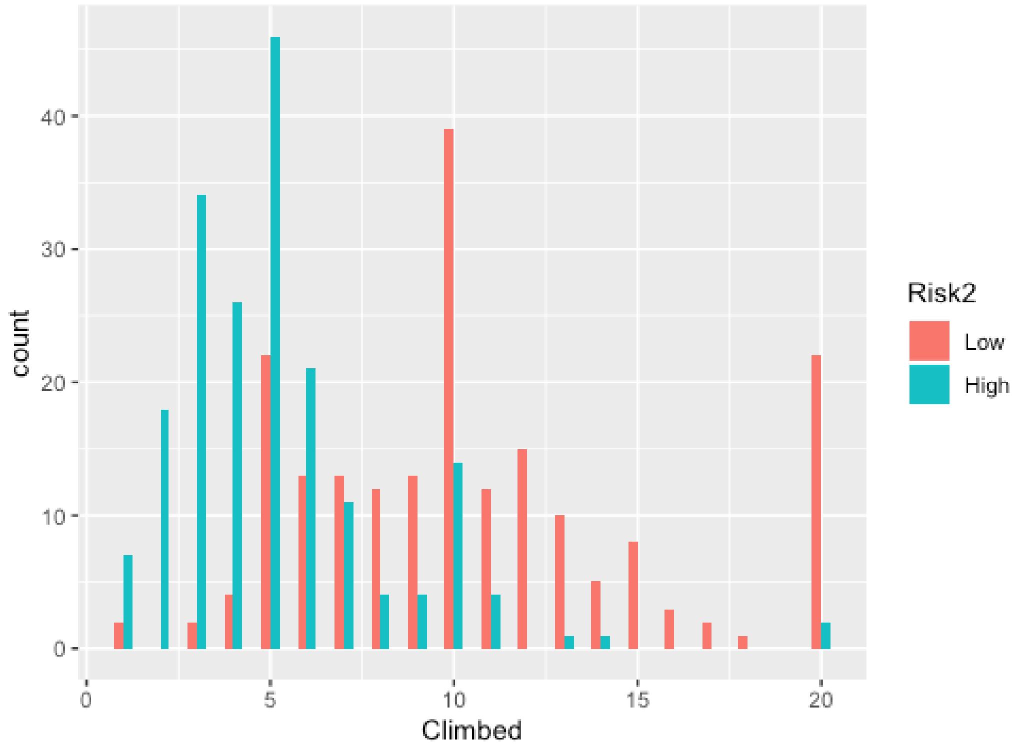

Figure 6 - Distribution of observations to risk

We discuss both the descriptive and regression results for our main variable of interest, the approach, in the next section.

5.2 Regression results

Column 1 of Table 3 (Model 1) contains the results of a model where we only include game-specific control variables (sunk costs, risk, and time used). Column 2 presents the results of a model where we include controls for socio-demographics, risk preferences, and experience of backcountry skiing. By default, the Tobit regression model does not follow the R-squared setup of the OLS-models. Instead, we estimated a Pseudo R-squared as our goodness of fit parameter. It is not uncommon for these types of R-squares to be considerably smaller than those of the regular R-squares. Like the R-squared of the OLS model however, a higher Pseudo R-squared indicates a better fit of the model but should be interpreted with great caution. Based on our Pseudo R-squared for both models, 0.0873 and 0.096 respectively, the second model thus has a slightly better fit to the data.

The data in table 3 represents coefficients from the estimations, with p-values in parentheses. Coefficients from a Tobit regression can be interpreted similarly to an OLS regression. In other words, the coefficient represents the increase in steps climb associated with a unit increase in the independent variable.

Table 3 - Effects of sunk costs and risk on risk-taking behaviour: Tobit regression results

Variable		Model 1	Model 2
Approach (reference short)			
	Medium	0.018	0.029
		(0.968)	(0.945)
	Long	- 0.507	- 0.434
		(0.269)	(0.326)
Risk (reference low)			
	High	- 5.522	- 5.406
		(< 0.001)	(< 0.001)
Time used (reference below 25%)			
	25% - 50%	- 1.072	- 1.137
		(0.050)	(0.036)
	50% - 75%	- 1.332	- 1.393
		(0.014	(0.010)
	> 75%	- 1.815	- 1.907
		(< 0.001)	(< 0.001)
Age (reference equal to or below 22)			
	Older than 22		- 0.770
			(0.212)
Male (Reference female)			0.995
			(0.290)
Experience (Reference No experience)			0.105
			(0.875)
General risk preferences			0.649
			(< 0.001)
Understanding of the game			0.457
			(0.520)
Understanding of probabilities			0.775
			(0.208)

Observations: Total: 391 Left-censored: 9 Uncensored: 358 Right-censored: 24

The study aimed at testing the hypothesis that behavioural sunk costs increase risk-taking behaviour. As can be seen in Table 3, we find no support for this hypothesis. The coefficients on both medium and long approach are small and insignificant in both models.
Figure 8 shows the distribution of steps climbed at the different approach levels. As can be seen in the figure, variations in the approach lengths do not produce any clear pattern.
It may be noted that, although we do not find any effect of time invested in the approach to the mountain, we do find a significant effect of time invested in the game (this result also holds when using continuous variables but is more clearly presented when using categories). We divided the game into four stages with the first quarter being our reference level. Across all time categories, the coefficients exhibit negative relations to the dependent variable to a rising extent. Being in the latter stages of the game thus making the participant less likely to take another step, as opposed to the first quarter. This implies that the less time the participant has left in his time bank, the more risk-averse he becomes. Another interesting finding is that we observe peaks in the number of steps climbed at levels 5, 10 and 20, as can be observed from Figure 7.

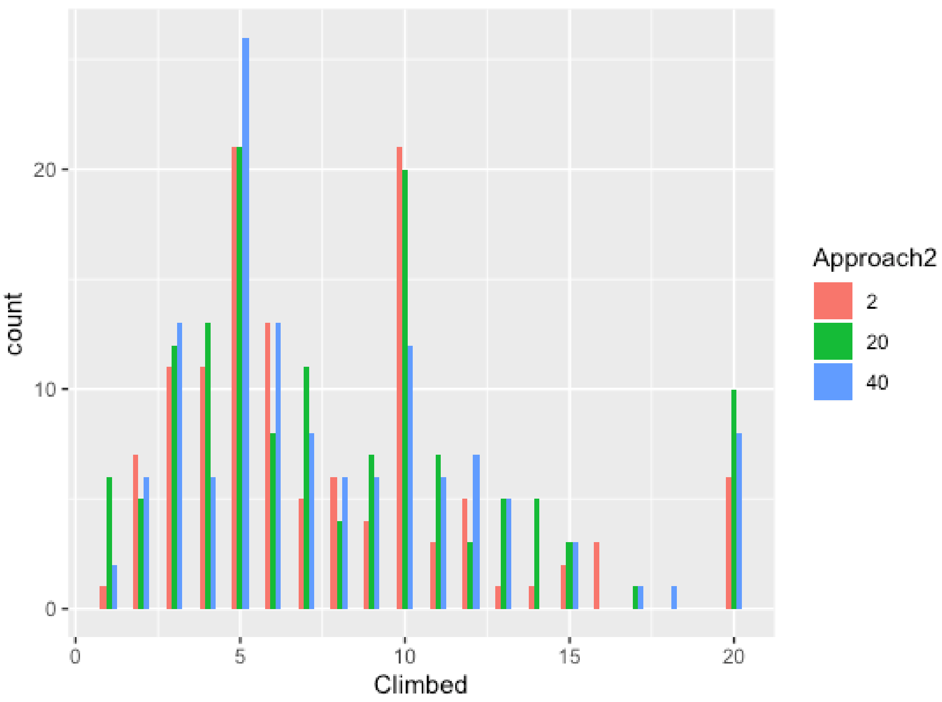

Figure 7 - Distribution of observations to steps climbed

We find relatively strong results for risk level in both models. More specifically, an increase in the risk level from five per cent to 10 per cent reduces the average climb by about 5 steps. This goes to show that the participants react to the increased risk. This is supported by the fact that there is a positive correlation between general risk preferences and the number of steps climbed, which is to be expected as a more risk-seeking individual will want to climb further given the constant level of risk. We have elected to use only the general risk preferences, as the experiment cannot be interpreted as an experiment of backcountry skiing. Further, neither financial $(p = 0.226)$ nor sporting risk $(p = 0.08)$ appear to be correlated to the number of steps climbed, whereas the general risk preferences are.

We find no effect of gender in our regression. This result is not a consequence of that we control for risk preferences. Men in our sample are significantly more willing to take risk than women $(t = -4.172, p < 0.001)$. However, they do not, on average, climb higher than women do $(t = 1.095, p = 0.290)$. Additionally, we were unable to find any age effects, which potentially could be explained similarly to the lack of gender effects.

Further, within our model, we analysed whether peoples understanding of probabilities would have an effect. We did this by making a dummy variable for those who did and those who did not answer the questions about probabilities correctly. Similarly, we tested whether participants before playing the game itself grasped the concept of it by asking several questions regarding potential payoffs. In either case, the results showed insignificant results, meaning that whether they understood the game and the probabilities did not affect the number of steps climbed.

6 Discussion

In this paper, we tested the hypothesis that BSCs increase risk-taking behaviour. We find no support for this hypothesis. Our results are consistent with those of the Friedman et al. (2007) experiment of behavioural sunk cost effects in risky decisions. Similar to our experiment, Friedman et al. (2007) encountered surprisingly small and insignificant sunk-cost effects. In terms of click differences, which is the closest sunk-cost predictor to the one we used, they found a small overall reverse sunk-cost effect, although not significant. They were able to find a more significant sunk-cost effect in one of the cases (case 1), although the effect was small, and thus did not generate much proof to the theory of the sunk-cost effect. These are similar results to the ones we observed in our analysis, where the Approach-variable yielded insignificant, small effects, and our relative sunk-costs (measured by the Time-left variable) showed reverse sunk-cost effects. The relative reverse sunk-costs is the time spent as a proportion of the overall time-budget. Further, Zeelenberg and van Dijk (1997) also found results of a reverse sunk-cost effect, where the incurred behavioural sunk-costs appeared to increase risk-aversive choices. This finding corresponds well with our results, in which an increased level of risk resulted in substantially fewer steps climbed.
At last, Sweis et al. (2018) were able to find significant effects of BSCs, in which further enhancement to prior investments lead to a continuously stronger sunk cost effect.

As can be observed from the studies aforementioned, the sunk-cost effects exhibit mixed findings. In our case, we did not find a significant sunk-cost effect. In terms of both sunk costs and risk, our data thus seem more compatible with the Neoclassical Microeconomic Theory than that of the Prospect Theory. There are several reasons as to why that might be the case. First and foremost, our sunk costs were based on time and effort, whereas the game itself was based on monetary rewards. Based on mental accounting, it is thus feasible that the participants did not place the time invested on the approach in the same mental account as that of the investment of climbing. This result is consistent with the findings of Soman (2001) which states that individuals fail to consider sunk costs in the form of time as highly as monetary sunk costs.
Additionally, due to a lack of information in the dataset, we are unable to observe time per

step between the various approaches, and the sunk cost thus is purely related to the number of steps before climbing the mountain, rather than time spent for the same distance. We are therefore unable to find results for time, but rather only for effort in relation to the sunk costs. It may be noted that the participants generally appear to converge towards certain "milestones" (5, 10 and 20), this might be explained by other psychological drivers in which we have not tested for in the current analysis. As for both levels of risk, we observed that the mean number of steps climbed (low = 10.49, high = 5.19) were quite a bit lower than that of the optimal strategy (low = 20, high = 10). This implies that people generally are risk averse.

A weakness of our data is the fact that some groups are overrepresented. In terms of age, we cannot measure various effects this might have, as all participants were cantered around their 20s. Gender effects are also something that holds inadmissible results, too few men were included in the sample. To get a more exact understanding of these effects in future projects, a larger sample size is necessary, preferably with a more diverse sample. Additionally, as we were unable to find a sunk-cost effect in our data, a more substantial measurement of sunk-costs is in order. It is worth mentioning that the recruitment of psychology students is to some extent stigmatised within the economic community as psychological studies tend to set a goal of "tricking" the participants. We did, however, inform them that this was not the case and made it clear that our research would be deemed inadmissible if that was the case, and as this was a pilot project, we deemed it adequate for our experiment. It is important to note that the experiment does not capture effects of sunk costs and risk related to actual avalanches, but is rather an illustration of these effects, and is a small step on the way to understanding the risk decision-making caused by sunk costs in these types of terrain.

7 Summary and conclusion

We have in this thesis evaluated the effects of risky decision-making to the sunk cost fallacy, based off of data collected from an economical experiment held at the start of 2020. The evaluation considers 65 psychology students, all in the second year of their undergraduate studies. The participants were given the task of climbing a virtual mountain with varying levels of approach steps before reaching the foot of the mountain – these were considered the sunk cost measurements of our analysis. Each trial was affiliated with a given level of risk where every mountain contained 20 steps. The participants were given a 20-minute time-budget for the experiment and were asked to fill out surveys before the game, and afterwards. A Tobit model was elected as the method of choice to deal with the censoring, as well as the ID-clustering of the data.

We did not find support for the hypothesis that BSCs increases risk-taking behaviour but did however find indications of relative reverse sunk cost effects concerning the time was left of the game. Throughout the game, the effect increased in significance, and the negative effect became more resolute, as observed in table 3. Additionally, we conducted a risk assessment of both the risks related to the game, as well as the general risk preferences stated by the participants. We found fairly predictable results that conform well with previous literature; particularly that people expose themselves to less risk when the level of risk increases, and that more risk-seeking individuals accept more risk. Both of these effects correspond to the risk-aversion aspect of our theories. We were unable to find any significant effects of either age or gender in our analysis, which in turn might stem from an over-representation of females and young individuals in our sample. This is also the case for the experience-variable. Further, we evaluated the data in relation to both comprehensions of the probabilities related to the game, as well as the general understanding of the game itself. None of these factors was significant.

As this was a pilot project, further research within this field will come, in which this analysis will serve as a foundation. For further analysis, it might be interesting to look further into the spikes we observe in the number of steps climbed at the 5, 10 and 20-intervals. Additionally, increasing the sunk cost might be worth looking further into, as it might we might see a bigger effect as participants are affected in a larger degree. It might be difficult for the participants to comprehend the sunk cost effects as both effects are in relation to time, but one of them is priced. It should be interesting to see whether there are more transparent effects if both investments were of the same category. There are also several other factors determining risk-taking behaviour, which would be interesting to test, like social effects, more individual-specific characteristics, and further investigation into risk aversion, which surely will be analysed in future extensions of the project. Further, it might be useful for future projects to consider a larger and more diversified sample pool to observe more accurate individual-specific characteristics and to see whether experience plays a part in risk-taking decisions. Furthermore, getting more individual-specific data might help better evaluate risky behaviour.

8 References

Arkes, H. R., & Blumer, C. (1985). The psychology of sunk cost. *Organizational Behavior and Human Decision Processes, 35*(1), 124-140. doi:10.1016/0749-5978(85)90049-4

Ashraf, N., Berry, J., & Shapiro, J. M. (2010). Can Higher Prices Stimulate Product Use? Evidence from a Field Experiment in Zambia. *American Economic Review, 100*(5), 2383-2413. doi:10.1257/aer.100.5.2383

Bernheim, B. D., & Rangel, A. (2007). Toward Choice-Theoretic Foundations for Behavioral Welfare Economics. *American Economic Review, 97*(2), 464-470. doi:10.1257/aer.97.2.464

Birkeland, K. W., Greene, E. M., & Logan, S. (2017). In Response to Avalanche Fatalities in the United States by Jekich et al. *Wilderness & Environmental Medicine*, *28*(4), 380-382. doi:10.1016/j.wem.2017.06.009

Buelow, M. T. (2015). Predicting Performance on the Columbia Card Task: Effects of Personality Characteristics, Mood, and Executive Functions. *Assessment*, *22*(2), 178-187. doi:10.1177/1073191114539383

Campbell, J. A., Samartgis, J. R., & Crowe, S. F. (2013). Impaired decision making on the Balloon Analogue Risk Task as a result of long-term alcohol use. *Journal of Clinical and Experimental Neuropsychology, 35*(10), 1071-1081. doi:10.1080/13803395.2013.856382

Chung, S., & Cheng, K. (2018). How does cognitive dissonance influence the sunk cost effect? *Psychology Research and Behavior Management, 11*, 37-45.

Croson, R. (2005). The Method of Experimental Economics. *International Negotiation, 10*(1), 131-148. doi:10.1163/1571806054741100

Dohmen, T. J., Falk, A., Huffman, D., Sunde, U., Schupp, J., Macro, I., . . . Rs: Gsbe, D. (2011). Individual risk attitudes: Measurement, determinants and behavioral consequences. *Journal of the European Economic Association, 9*(3), 522-550. doi:10.1111/j.1542-4774.2011.01015.x

Figner, B., Mackinlay, R. J., Wilkening, F., & Weber, E. U. (2009). Affective and Deliberative Processes in Risky Choice: Age Differences in Risk Taking in the Columbia Card Task. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 35*(3), 709-730. doi:10.1037/a0014983

Friedman, Pommerenke, Lukose, Milam, & Huberman. (2007). Searching for the sunk cost fallacy. *A Journal of the Economic Science Association, 10*(1), 79-104. doi:10.1007/s10683-006-9134-0

Fukunaga, R., Brown, J. W., Bogg, T., & Fukunaga, R. (2012). Decision making in the Balloon Analogue Risk Task (BART): anterior cingulate cortex signals loss aversion but not the infrequency of risky choices. *Cognitive, affective & behavioral neuroscience, 12*(3), 479-490. doi:10.3758/s13415-012-0102-1

Humphreys, K. L., Lee, S. S., & Tottenham, N. (2013). Not all risk taking behavior is bad: Associative sensitivity predicts learning during risk taking among high sensation seekers. *Personality and Individual Differences, 54*(6), 709-715. doi:10.1016/j.paid.2012.11.031

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision Under Risk. *Econometrica, 47*(2), 263. doi:10.2307/1914185

Kahneman, D., & Tversky, A. (1984). Choices, values, and frames. *American Psychologist, 39*(4), 341-350. doi:10.1037/0003-066X.39.4.341

Knox, R. E., & Inkster, J. A. (1968). Postdecision dissonance at post time. *Journal of Personality and Social Psychology, 8*(4, Pt.1), 319-323. doi:10.1037/h0025528

Leeds, D. M., Leeds, M. A., & Motomura, A. (2015). Are sunk costs irrelevant? Evidence from playing time in the national basketball association. *Economic Inquiry*. doi:10.1111/ecin.12190

Lejuez, C. W., Aklin, W. M., Jones, H. A., Richards, J. B., Strong, D. R., Kahler, C. W., & Read, J. P. (2003). The Balloon Analogue Risk Task (BART) Differentiates Smokers and Nonsmokers. *Experimental and Clinical Psychopharmacology, 11*(1), 26-33. doi:10.1037/1064-1297.11.1.26

Lejuez, C. W., Read, J. P., Kahler, C. W., Richards, J. B., Ramsey, S. E., Stuart, G. L., . . . Brown, R. A. (2002). Evaluation of a Behavioral Measure of Risk Taking: The Balloon Analogue Risk Task (BART). *Journal of Experimental Psychology: Applied, 8*(2), 75-84. doi:10.1037/1076-898X.8.2.75

Phillips, O., Battalio, R., & Kogut, C. (1991). Sunk and Opportunity Costs in Valuation and Bidding. *Southern Economic Journal, 58*(1), 112. doi:10.2307/1060037

Roodhooft, F., & Warlop, L. (1999). On the role of sunk costs and asset specificity in outsourcing decisions: a research note. *Accounting, Organizations and Society, 24*(4), 363-369. doi:10.1016/S0361-3682(98)00069-5

Simon, H. A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics, 69*(1), 99-118.

Soman, D. (2001). The mental accounting of sunk time costs: why time is not like money. *Journal of Behavioral Decision Making, 14*(3), 169-185. doi:10.1002/bdm.370

Staw, B. M. (1976). Knee-deep in the big muddy: a study of escalating commitment to a chosen course of action. *Organizational Behavior and Human Performance, 16*(1), 27-44. doi:10.1016/0030-5073(76)90005-2

Sweis, B. M., Abram, S. V., Schmidt, B. J., Seeland, K. D., Macdonald, A. W., Thomas, M. J., . . . Sweis, B. M. (2018). Sensitivity to "sunk costs" in mice, rats, and humans. *Science (New York, N.Y.), 361*(6398), 178-181. doi:10.1126/science.aar8644

Tan, H.-T., & Yates, J. F. Y. (1995). Sunk cost effects: The influences of instructions and future return estimates. *Organizational Behavior and Human Decision Processes, Volume 63, Issue 3*, Pages 311-319. doi:https://doi.org/10.1006/obhd.1995.1082

Thaler, R. (1980). Toward a Positive Theory of Consumer Choice. *Journal of Economic Behavior & Organization, 1*, 39-60.

Thaler, R. (1985). Mental Accounting and Consumer Choice. *Marketing Science, 4*(3), 199-214. doi:10.1287/mksc.4.3.199

Thaler, R. (1999). Mental accounting matters. *Journal of Behavioral Decision Making, 12*(3), 183-206. doi:10.1002/(SICI)1099-0771(199909)12:3<183::AID-BDM318>3.0.CO2-F

Thaler, R., & Johnson, E. (1990). Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice. *Management Science, 36*(6), 643-660. doi:10.1287/mnsc.36.6.643

Van Dijk, E., & Zeelenberg, M. (2003). The discounting of ambiguous information in economic decision making. *Journal of Behavioral Decision Making, 16*(5), 341-352. doi:10.1002/bdm.450

Vigil-Colet, A. (2007). Impulsivity and decision making in the balloon analogue risk-taking task. *Personality and Individual Differences, 43*(1), 37-45. doi:10.1016/j.paid.2006.11.005

Von Neumann, J., & Morgenstern, O. (1944). Theory of Games and Economic Behavior. *Princeton University Press*, 674. Retrieved from http://jmvidal.cse.sc.edu/library/neumann44a.pdf

Whyte, G. (1993). Escalating Commitment in Individual and Group Decision Making: A Prospect Theory Approach. *Organizational Behavior and Human Decision Processes, 54*(3), 430-455. doi:10.1006/obhd.1993.1018

Zeelenberg, M., & van Dijk, E. (1997). A reverse sunk cost effect in risky decision making: Sometimes we have too much invested to gamble. *Journal of Economic Psychology, 18*(6), 677-691. doi:10.1016/S0167-4870(97)00029-9

9 Appendices

9.1 Appendix A – The Von Neumann-Morgenstern utility representation theorem

The theorem is structured with n possible prizes an individual can obtain by participating in the lottery. The prizes are denoted as $x_1, x_2, \dots, x_n$, and are ordered by ascending desirability. There is an existing probability, p_i, that would make an individual indifferent between a guaranteed prize x_i and a gamble offering x_n with the probability p_i and x_1 with the probability $1 - p_i$. It is reasonable to assume that p_i will be higher the greater x_i is – the better x_i, the greater the chance of winning x_n will be in order for the individual to be willing to gamble. In other words, p_i is a good indication of the desirability of x_i. The theorem defines the utility of x_i as the expected utility of the gamble the individual considers equal to x_i, so that

$$U(x_i) = p_i U(x_n) + (1 - p_i) U(x_1) \tag{1}$$

In order to maximise the utility, suppose that a utility index p_i is assigned to every prize, x_i. Assume that this utility index ranges between $p_1 = 0$ to $p_n = 1$. By using these indices, we are able to show that rational individuals choose among gambles based on their expected utilities.

Consider two gambles, in which A offers x_2 with the probability a and x_3 with the probability $1 - a$, and B offers x_4 with the probability b and x_5 with the probability $1 - b$. An individual will based off of the Von Neumann-Morgenstern theorem choose A only if it exceeds B, and we have the gambles:

$$Expected\ utility\ of\ A = \ E_A[U(x)] = aU(x_2) + (1 - a)U(x_3),$$

$$Expected\ utility\ of\ B = E_B[U(x)] = bU(x_4) + (1-b)U(x_5) \quad (2)$$

Substituting the utility index numbers, we obtain

$$E_A[U(x)] = ap_2 + (1-a)p_3,$$

$$E_B[U(x)] = bp_4 + (1-b)p_5 \quad (3)$$

As stated, an individual will only prefer A to B if $E_A[U(x)] > E_B[U(x)]$. The individual is indifferent between x_2 and a gamble yielding x_1 with a probability of $1 - p_2$ and x_n with the probability p_2. This can be incorporated into equation (3) by substituting gambles involving x_1 and x_n for all utilities. Von Neumann and Morgenstern solved the problem algebraically, and concluded that A equals a gamble yielding x_n with a probability $ap_2 + (1-a)p_3$, and B equals a gamble yielding x_n with a probability of $bp_4 + (1-b)p_5$. Consequently, the individual will choose gamble A only if

$$ap_2 + (1-a)p_3 > bp_4 + (1-b)p_5 \quad (4)$$

The individual thus chooses the gamble providing the highest expected Von Neumann-Morgenstern utility.

9.2 Appendix B – Optimal strategy

The optimal strategy is based on the expected gain and the expected loss. The expected gain is based on the risk and the gain, so the expected gain for the low-risk games will be 0.95*1, whereas the risk of succeeding the step climbed is 95% (90% in high-risk games), multiplied by the gain of the step taken.

The expected loss is based on the expected probability of falling (0.05 at low risk and 0.1 in high risk) and the possible loss. This is based on the previous steps in each of the games, so at step 4 the risk is to lose the 3 steps that are already climbed.

In table 4 below we see that the expected gain and expected loss meet at 20 steps in the low-risk game, and the optimal strategy in low-risk games will therefore be to climb to the top. In high-risk games, we see that expected gain and expected loss are the same at 10 steps, and here the optimal strategy will be to just climb half the mountain. If the participant chooses to climb higher than this, will the expected loss be higher than the expected gain of the game, and therefore not be profitable.

Table 4 - Optimal strategy

Steps	Low Risk		High Risk	
	Expected Gain	Expected Loss	Expected Gain	Expeted Loss
1	0,95	0	0,9	0
2	0,95	0,05	0,9	0,1
3	0,95	0,1	0,9	0,2
4	0,95	0,15	0,9	0,3
5	0,95	0,2	0,9	0,4
6	0,95	0,25	0,9	0,5
7	0,95	0,3	0,9	0,6
8	0,95	0,35	0,9	0,7
9	0,95	0,4	0,9	0,8
10	0,95	0,45	0,9	0,9
11	0,95	0,5	0,9	1
12	0,95	0,55	0,9	1,1
13	0,95	0,6	0,9	1,2
14	0,95	0,65	0,9	1,3
15	0,95	0,7	0,9	1,4
16	0,95	0,75	0,9	1,5
17	0,95	0,8	0,9	1,6
18	0,95	0,85	0,9	1,7
19	0,95	0,9	0,9	1,8
20	0,95	0,95	0,9	1,9

9.3 Appendix C – Instructions to the game

Welcome to the game, "Run to (and up) the Hills"!

In this game, your task is to climb mountains in order to earn money. Each mountain has 20 "steps" to the summit. You earn 1 NOK for each step you climb. Your task is to decide how high to climb on each mountain. You decide to either climb or go down on each step.

Commands:

Climb: $\boxed{\text{C}}$ $\boxed{\text{U}}$, $\boxed{\text{Shift}}$ for 2 seconds

Stop/Go to the next mountain: $\boxed{\text{D}}$ and $\boxed{\text{Shift}}$ for 2 seconds

When you either reach the summit of a mountain, or decide to go down, you move on to the next mountain, and again decide how high to climb. The game ends after 20 minutes. Your total earnings is the sum of the money that you have earned on each mountain plus 50kr for the participation.

But there are of cause some catches:

Catch 1: But mountaineering is a risky activity. If you are unlucky and make a "bad" step, you will fall and tumble down the mountain. If you fall of the mountain, you lose all of your earnings on that particular mountain.

A fall on one mountain does not affect your previous earnings. If you do fall, you move on to the next mountain, and once again decide how high to climb.

Each of the steps on your route up a mountain is potentially a "bad step". There is no way of knowing which steps are "good" and which are "bad", but the probability that a step is "bad", is constant along your route. You will get to know the probability of a "bad" step for each mountain, and this probability will stay constant.

Catch 2: To get to the mountain you first have to climb a few "approach" steps. You climb the approach steps in the same way as you climb the rest of the mountain, by pressing C, U and shift for 2 seconds. The approach steps are completely safe (no risk of falling down), but you do not earn anything from climbing them either.

Good luck!

9.4 Appendix D – RTH-pilot questionnaire

1. PRE-EXPERIMENT – Introductory questions (Understanding the game)

1.1. How many NOK can you maximally obtain for a mountain given that you reach the summit?

1.2. Given that you have reached the summit for three mountains. How many NOK have you obtained?

1.3. Imagine you have reached the summit for three mountains. On the fourth mountain you fall down at the seventh step. How many NOK have you obtained up until now?

1.4. A urn contains **20 balls**: **18 blue and 2 red**. Imagine that you now draw a random ball **100 times**. After each draw, you put the ball back into the urn before drawing another. **How many** of the 100 balls do you expect to be red?

1	5	10	15	20	25	30	35	40	45	50
55	60	70	75	80	85	90	95	100		

1.5. Imagine that you are playing Run to (and up) the hills! You have completed the predetermined steps and have reached the foot of the mountain. You have climbed 10 steps with a 10% probability that each step is "bad" (**2 red** and **18 blue** balls in the urn) You now choose to take yet another step. What is the probability of falling down?

1%	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%
55%	60%	65%	70%	75%	80%	85%	90%	95%	100%	

2. POST EKSPERIMENT

2.1 What is your gender? Man/Woman/Other

2.2 How old are you? (18, 19, 20, 21, 22, 23, 24, 25, >25)

2.3 Attitude to risk (Dohmen et al., 2011) (0 = not willing to take on risk at all, 10 = very eager to take on risk)

2.3.1 Generally speaking, are you a person who is ready to take on risk, or are you a person that tries to avoid it?

0 1 2 3 4 5 6 7 8 9 10

2.3.2 How do you view yourself in terms of financial risk (with money), are you a person who likes risk, or do you try to avoid it?

0 1 2 3 4 5 6 7 8 9 10

2.3.3 In terms of risk related to sports and outdoor activities, are you a person that likes risk, or do you try to avoid it?

0 1 2 3 4 5 6 7 8 9 10

2.4 How many seasons have you been an «active mountain climber»?

“Mountain climber” in this sense is a person that spends a lot of time walking in avalanche terrain (Not your everyday ski resort). The individual may be skiing, using a snowboard, walking on snowshoes, using a snowmobile, etc.) With “Active” we mean that the individual at least made one trip throughout the season.

1. None – I don’t ascend mountains at all
2. Less than one season
3. 1-2 seasons
4. 3-4 seasons
5. 5-6 seasons
6. 7-8 seasons
7. 9-10 seasons
8. More than 10 seasons

2.5 How many days per season do you usually ascend mountains? Use a representative season from the last five years.

1. None – I don’t ascend mountains at all
2. Less than 1 day/season
3. 1-10 days/season
4. 11-20 days/season
5. 21-30 days/season
6. 31-40 days/season
7. 41-50 days/season
8. More than 50 days/season